Nature Environment and Pollution Technology
An International Quarterly Scientific Journal
p-ISSN: 0972-6268
e-ISSN: 2395-3454
Vol. 16 No. 1 pp. 37-43 2017

Original Research Paper **Open Access**

Impact on Population Exposure to PM2.5 by its Source Factors in China: Provincial Panel Data Analysis

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 06-03-2016
Accepted: 16-04-2016

Key Words:
Population-weighted PM2.5 exposure
Energy consumption
Highway length
Construction area
Panel data analysis

ABSTRACT

Studying the impacts of PM2.5 concentrations is critical due to health risks associated with PM2.5. This study analyses 2001-2010 provincial panel data of population-weighted PM2.5 exposure and its main sources in China to identify any correlations that may exist. The results show that energy consumption, highway length, and construction positively affect population-weighted PM2.5 exposure, but vehicle possession has a negative effect. Increasing energy consumption, highway length, and construction areas by 1% resulted in 0.11%, 0.12%, and 0.06% increases to PM2.5 population exposure, respectively. However, when vehicle possession increased by 1%, population exposure to PM2.5 decreased by 0.20%. Highway length may be a very important factor for the increased PM2.5 concentrations in China. Therefore, China should consider national and provincial factors when developing policies to control PM2.5 emissions.

INTRODUCTION

PM2.5 (fine particulate matter with aerodynamic diameter smaller than or equal to 2.5μm) is an air pollutant that negatively affects human health through enhanced morbidity and mortality rates (Hodas et al. 2013, Laden et al. 2006, Dockery et al. 1993, Krewski 2009, Pope et al. 2002, 2004, Lepeule et al. 2012). Long-term PM2.5 exposure can contribute to health risks, even at relatively low concentrations (Crouse 2012). Additionally, adverse weather conditions in China may result in short-term, acute PM2.5 exposure for Chinese citizens (Zhang et al. 2011, Zhang et al. 2013a, Pui et al. 2014, Xu et al. 2013, Wang et al. 2013). With new national air quality standards taking effect in January 2016 (MEPC 2012), PM2.5 has become a major issue for future pollution control in China.

Recent research has divided PM2.5 into two categories (CCICED 2012): One is from primary sources, which are direct emissions, the other is from secondary sources by atmospheric chemical transformation that oxidize gas phase precursors to form new particles, such as sulphate, nitrate, and organic matter. PM2.5 concentrations vary depending on factors such as location, time, and meteorological conditions (Tang et al. 2006), but in general the major PM2.5 sources are consistent with recent findings. Likely PM2.5 sources were identified by characterizing aerosol speciation in Beijing based on a positive matrix factorization model. Soil dust, coal combustion, biomass burning, traffic and waste incineration emission, industrial pollution, and secondary inorganic aerosol were found to be the six main sources of PM2.5, they had an annual mean PM2.5 contribution of 16%, 14%, 13%, 3%, 28%, and 26% (Zhang et al. 2013b). Huang et al. used a positive matrix factorization model to understand the major sources of PM2.5 and their temporal and spatial variations in Shenzhen. They found that secondary sulphate, vehicular emission, biomass burning, and secondary nitrate are major sources that contributed 30.0%, 26.9%, 9.8% and 9.3% to total PM2.5, respectively (Huang et al. 2014). A new study of PM2.5 sources was carried out on three Chinese cities, demonstrating that construction dust and soil sand dust contributed 45.35%; industry dust, coal-combusted smoke, and vehicle emissions collectively contributed 31.83%; biomass burning dust contributed 13.57% (Gao et al. 2013). Hence, we can conclude that the main sources of PM2.5 include energy combustion, vehicle exhausting, road dust floating, and construction dust emission.

The above studies focused on the PM2.5 concentrations and chemical compositions in one or more Chinese cities. It is important to understand the contributions of major PM2.5

sources at a national level so that China can design effective PM2.5 reduction strategies. However, studies evaluating the relationship between PM2.5 population exposure and PM2.5 sources based on national, long-term, systematic observation are rare. This study fills that knowledge gap by evaluating the data with a panel data analysis method.

METHODS

To identify the relationship between population-weighted PM2.5 exposure and its driving forces in China, we performed panel data analysis using the regression method. The panel data analysis has four steps: panel unit root analysis, panel cointegration analysis, selecting regression method by F-test, and Hausman test. Ordinary Least Squares (OLS) were applied for pooled data analysis in the selected regression method.

The explained variable in the study for panel data analysis is the logarithmic population-weighted PM2.5 exposure (PM) with the unit of micrograms per cubic meter. Explanatory variables in the panel data include the logarithmic Energy consumption (LnEN), logarithmic Highway length (LnHI), logarithmic Construction area (LnCO), the logarithmic Vehicle Possession (LnVE). EN is the total energy consumption by region in 1,000,000 tons of standard coal equivalent; this represents coal combustion, biomass burning, and secondary inorganic aerosol. HI is the total collective highway length by region in kilometres; this represents road dust and traffic emissions. CO is the building construction floor space by region in 10,000 square meters; this demonstrates construction dust emissions. VE is the civil vehicle possession in 10,000 units; this reflects vehicle emissions.

Panel data covered 29 Chinese provinces from 2001 to 2010: Shandong (SD), Henan (HEN), Hebei (HEB), Jiangsu (JS), Anhui (AH), Hubei (HUB), Sichuan (including Chongqing, SC), Guangxi (GX), Tianjin (TJ), Beijing (BJ), Jiangxi (JX), Hunan (HN), Shanghai (SH), Yunnan (YN), Shaanxi (SAX), Shanxi (SX), Guangdong (GD), Guizhou

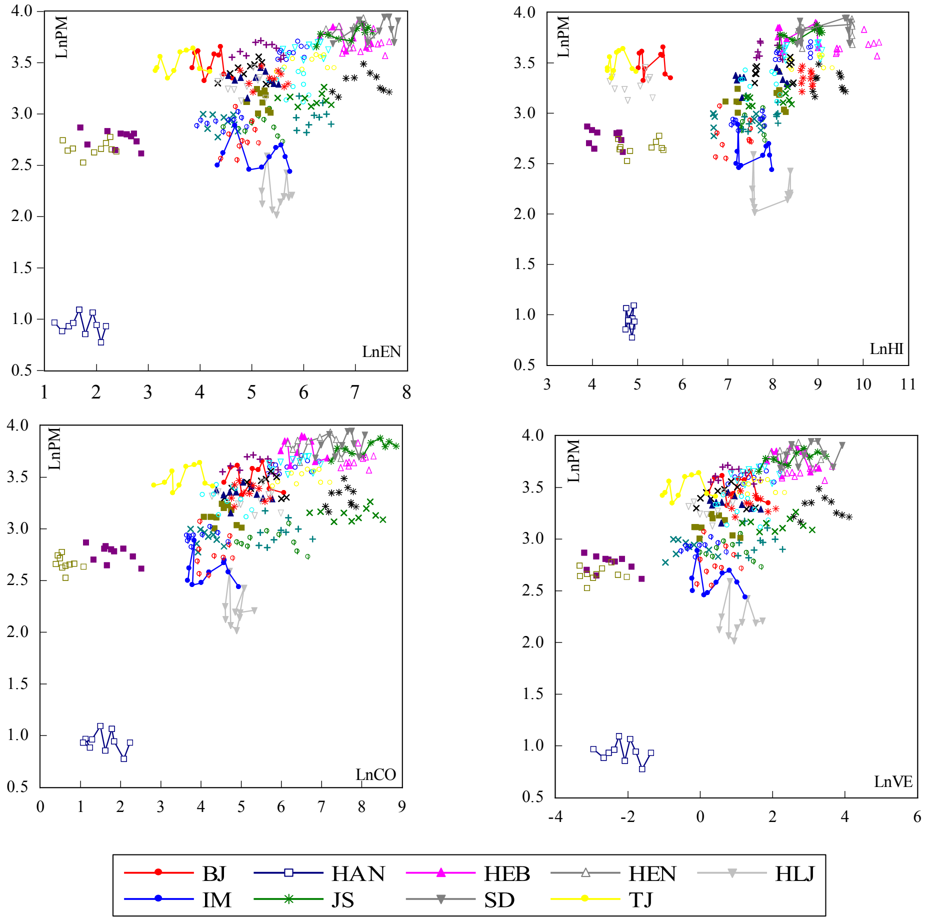

Fig. 1: Scatter graphs of explanatory variables and explained variable in logarithmic form.

Table 1: Descriptive statistics of time-series population-weighted PM2.5 exposure (μg/m^3) in 29 provinces in China.

Province abbreviation	Descriptive statistics				Province abbreviation	Descriptive statistics			
	Min.	Max.	Ave.	Std.		Min.	Max.	Ave.	Std.
SD	40.00	51.94	46.16	4.73	SX	22.48	30.71	26.88	2.97
HEN	38.11	51.02	45.09	4.04	GD	23.70	32.71	27.33	2.82
HEB	36.97	49.23	43.81	4.45	GZ	20.19	25.64	22.86	2.00
JS	38.69	48.32	43.94	2.87	ZJ	21.51	26.12	23.16	1.42
AH	34.03	40.65	36.69	2.13	FJ	15.31	21.11	17.91	1.70
HUB	34.13	40.68	37.78	2.30	LN	16.78	23.93	19.52	2.24
SC	35.34	45.95	38.85	3.00	GS	16.04	20.08	18.56	1.40
GX	34.27	41.06	37.58	2.45	XJ	16.83	20.47	18.57	0.99
TJ	28.40	38.06	32.92	3.45	NX	13.69	17.62	15.86	1.28
BJ	27.70	38.64	33.15	3.94	JL	12.79	21.52	16.00	2.64
JX	26.87	35.11	30.52	2.84	QH	12.52	16.07	14.40	0.99
HUN	30.31	35.62	33.03	2.09	IM	11.43	17.92	13.44	1.95
SH	22.94	31.79	26.94	2.67	HLJ	7.53	13.39	9.37	1.75
YN	24.87	32.05	28.51	2.28	HAN	2.17	2.98	2.57	0.24
SAX	23.36	31.47	28.08	2.20	Total	2.17	51.94	27.22	11.52

Table 2: The descriptive statistics of LnEN, LnHI, LnCO and LnVE for whole China.

	LnEN	LnHI	LnCO	LnVE
Mean	5.2545	7.5126	14.4753	10.1061
Median	5.3609	7.8288	14.5056	10.2339
Maximum	7.8249	10.3541	18.0672	13.3250
Minimum	1.1848	3.8811	9.5939	5.8731
Std. Dev.	1.4894	1.5601	1.8656	1.5793
Skewness	-0.7446	-0.7423	-0.5885	-0.6659
Kurtosis	3.3260	2.6152	3.1657	3.4025
Jarque-Bera	28.0805	28.4243	17.0706	23.3889
Probability	0.0000	0.0000	0.0002	0.0000
Sum	1523.7970	2178.6520	4197.8340	2930.7740
Sum Sq. Dev.	641.0591	703.3634	1005.8030	720.8223
Observations	290	290	290	290
Cross sections	29	29	29	29

(GZ), Zhejiang (ZJ), Fujian (FJ), Liaoning (LN), Gansu (GS), Xinjiang (XJ), Ningxia (NX), Jilin (JL), Qinghai (QH), Inner Mongolia (IM), Heilongjiang (HLJ), and Hainan (HAN). Tibet and other provinces were not included due to data scarcity. For consistency with PM2.5 data sources, Chongqing was included with Sichuan as new SC identifier.

Various methods allow us to pose the null hypothesis in a more natural form, and test whether or not the relationship between energy consumption, highway length, construction area, vehicle possession and PM2.5 exposure is consistent in the above-listed provinces. We propose a new model based on the STIRPAT model (Rosa & Dietz 1998, York et al. 2003). Considering that the logarithm can eliminate data heteroscedasticity and maintain data characteristics (Mukherjee et al. 1998), we analysed the logarithmic value of each variable. Therefore, Eq. 1 shows the empirical model containing four new explanatory variables in logarithm form.

$$Ln(PM_{i,t}) = C_{i,t} + \alpha_1 Ln(EN_{i,t}) + \alpha_2 Ln(HI_{i,t}) + \alpha_3 Ln(CO_{i,t}) + \alpha_4 Ln(VE_{i,t}) + \varepsilon_{i,t} \quad ...(1)$$

Here, i (i=1, …, 29) denotes the different Chinese provinces, t (t=2001,…,2010) represents the different periods from 2001 to 2010, $C_{i,t}$ is constant, and $\varepsilon_{i,t}$ is a stochastic error term that obeys normal distribution.

To determine the validity of Equation 1, we identified the mathematical relationship between each explanatory variable and population-weighted PM2.5 exposure in logarithmic form by making regresses on scatter graphs (Fig. 1). The results show that the logarithm explained the variable, and each logarithmic explanatory variable had a linear relationship.

Table 3: The results of tests for unit root in 1st difference.

Test Method	Statistic	Prob.***
Assumes common unit root process		
LLC	-25.1539	0.0000**
Assumes individual unit root process		
Im, Pesaran and Shin W-stat	-10.9931	0.0000**
ADF - Fisher Chi-square	665.9060	0.0000**
PP - Fisher Chi-square	815.5810	0.0000**

** $P<0.01$ (two-tailed tests)*** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.All variables are in natural logarithms (LN).

Table 4: The results of panel cointegration tests.

Method	Statistic	Prob.
Pedroni's test (within-dimension)		
Panel v-Statistic	-2.5245	0.0165***
Panel rho-Statistic	5.7374	0.0000**
Panel PP-Statistic	2.2210	0.0339***
Panel ADF-Statistic	1.9513	0.0594****
Pedroni's tests (between-dimension)		
Group rho-Statistic	7.2534	0.0000**
Group PP-Statistic	-7.8584	0.0000**
Group ADF-Statistic	-5.2429	0.0000**
Kao's test		
ADF	-6.2969	0.0000**

** $P<0.01$ (two-tailed tests)*** $P<0.05$ (two-tailed tests)****$P<0.10$ (two-tailed tests). The null hypothesis is that the variables are not cointegrated.

Table 5: F-test results.

Effects Test	Statistic	Prob. **
Cross-section F	8.5603	0.0012
Cross-section Chi-square	16.7028	0.0002

** $P<0.01$ (two-tailed tests)

Table 6: Hausman test results.

Test Summary	Chi-Sq. Statistic	Prob. **
Period random	33.2088	0.0000

** $P<0.01$ (two-tailed tests)

DATA ACQUISITION

We used ground-level population-weighted PM2.5 exposure data from 2000 to 2010 of aerosol optical depth (AOD) using satellite atmospheric aerosol remote sensing (Liu 2013, BMI & CIESIN 2013) because ground instruments in China are unavailable or offer limited information, and PM2.5 concentration sites are sparse or have only been established recently. Table 1 lists the descriptive statistics of raw population-weighted PM2.5 exposure in China.

The panel data of the explanatory variables of China's 29 provinces in 2001-2010 were collected from "China Statistical Year-book (NBS 2002-2011a)" and "China Statistical Yearbook of Energy (NBS 2002-2011b)" published by the National Statistics Bureau of China. Table 2 lists the nation-scope descriptive statistics of all logarithmic population-weighted explanatory variables.

Fig. 1 shows scatter graphs of the explanatory variables and explained variables in logarithmic form to explain the data trend of all provinces from 2001 to 2010.

RESULTS

Unit root test: To avoid the possibility of spurious regression, we employed four different unit root tests, including the Levin-Lin-Chu (LLC) test (Levin et al. 2002), Im-Pesaran-Shin (IPS) test (Im et al. 2003), ADF-Fisher test (Maddala & Wu 1999), and PP-Fisher test (Maddala & Wu 1999). Table 3 shows the tests' results; they indicate that the statistics significantly confirm that all variables were stationary at the 5% significance level in the 1st difference, which indicates that all series were I(1).

Panel cointegration test: The panel cointegration tests must be examined to determine whether variable regressions in the panel data are spurious. Moreover, it is appropriate to test the cointegrating relationship between the five variables. This study employs two categories of panel cointegration tests, the Pedroni's test (Pedroni 1999, 2004) and Kao's test (Kao 1999) from the EG two-step method.

As shown in Table 4, Pedroni's heterogeneous panel test results indicate that the null of no cointegration can be accepted at the 5% significance level, except for the panel ADF-statistic. However, Kao's test results show that the null of no cointegration can be accepted at the 1% significance level. Hence, there is a long-term stable equilibrium relationship between all variables.

Panel data regression estimate

F-test result: As listed in Table 5, the F-test (likelihood ratio test) statistic for the null of absence of cross-sections fix (fixed province-specific) effects is 212.85 > F0.05 (28,257) = 1.62 (Pearson & Hartley 1967), implying a rejection of the null hypothesis. Hence, we should select a fixed province-specific regression model instead of a pooled model.

Hausman test result: A Hausman test based on robust variance estimators was performed to test the strict exogeneity of explanatory variables on the basis of comparison within first-difference estimators. Table 6 shows that the value of the statistical probability was 0.0000 at the 5% level, implying a rejection of the strict exogeneity null hypothesis.

Table 7: The results of OLS Estimation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.5903	0.3318	4.7931	0.0000^{**}
Ln(EN)	0.1093	0.0527	2.0750	0.0390^{***}
Ln(HI)	0.1169	0.0287	4.0729	0.0001^{**}
Ln(CO)	0.0595	0.0441	1.3474	0.1790
Ln(VE)	-0.2027	0.0491	-4.1279	0.0000^{**}
Adjusted R-squared	0.9758	Durbin-Watson stat	2.0849	
F-statistic	363.8869	Prob(F-statistic)	0.0000^{**}	

** P<0.01 (two-tailed tests)*** P<0.05 (two-tailed tests)

Table 8: The fixed effects of provinces.

Fixed Effects (Cross)			
SD-C	0.5264	SX-C	0.1002
HEN-C	0.4911	GD-C	0.0816
HEB-C	0.5452	GZ-C	-0.1222
JS-C	0.4647	ZJ-C	-0.0679
AH-C	0.3146	FJ-C	-0.3310
HUB-C	0.2838	LN-C	-0.23835
SC-C	0.2442	GS-C	-0.3044
GX-C	0.4055	XJ-C	-0.2655
TJ-C	0.6739	NX-C	-0.2144
BJ-C	0.7109	JL-C	-0.3613
JX-C	0.1479	QH-C	-0.3376
HUN-C	0.1393	IM-C	-0.6161
SH-C	0.36813	HLJ-C	-0.9765
YN-C	0.1225	HAN-C	-1.9348
SAX-C	0.1501		

Here, we should select an individual fixed effect regression model instead of a random-effect model.

Panel OLS estimate: Our model is based on the regression between these five factors, as presented in Eq. 1. Table 7 presents the results of the transformation regression for models in this study. Furthermore, the fixed effects of the cross-sections can be listed in Table 8.

DISCUSSION

Panel OLS estimation: In Table 7, the OLS regression estimation of the fixed effects model shows that the coefficients of LnEN and LnHI had positive coefficients and were statistically significant at the 1% and 5% levels, respectively. Meanwhile, the independent variable of LnVE had a negative coefficient and was statistically significant at the 1% level. However, LnCO did not pass the t-test, which means they were not statistically significant in the OLS estimation. Fortunately, the OLS regression estimation fit reasonably, as indicated by the 0.0000 F-statistic. The Adjusted-R2 was 0.9758, which means that about 98% of the variation in the explanatory variable can be explained by the variation in the dependent variables. The D.W. statistic was 2.0849, which was in the zone of a non-autocorrelation problem (Durbin & Watson 1951).

Energy consumption, highway length, and construction can increase population PM2.5 exposure in China. When energy consumption, highway length, and construction area increased by 1% in China, population PM2.5 exposure increased by 0.11%, 0.12%, and 0.06%, respectively.

It is interesting that vehicle possession may decrease population PM2.5 exposure in China. When vehicle possession increased by 1% in China, population PM2.5 exposure decreased by 0.20%. Technological advances of newly produced vehicles may weaken vehicle contributes to PM2.5 concentration.

Highway length is a key factor for vehicle exhaust and increased PM2.5 concentrations. In the previous study, resuspended road dust and tailpipe emissions, which can explain the car ownership variable, were found to be the dominant mechanisms that significantly contributed to PM2.5 emission (Abu-Allaban et al. 2003). Another study on construction showed that 80% of fugitive PM2.5 emissions were attributable to the roadway excavation phase of construction (Reid et al. 2013).

The fixed effects of provinces: Table 8 demonstrates the differences in the provincial panel data analysis results. Shangdong, Hebei, Henan, and Jiangsu had relatively high PM2.5 exposure risks compared to other provinces between 2001 and 2010. However, Hainan, Heilongjiang, and Inner Mongolia displayed lower PM2.5 exposure risks. Of the tested provinces, Hainan had the lowest PM2.5 exposure risk, likely due to its island geographical features and tropical climate. Heilongjiang and Inner Mongolia had the second lowest PM2.5 exposure risk.

Beijing and Tianjin may be affected by other factors that influence PM2.5 concentration because they had 2.3012 and 2.2642 regression model constants, respectively. Fig. 1 displays this result; Beijing and Tianjin had higher LnPM values than many other provinces, and had relatively low

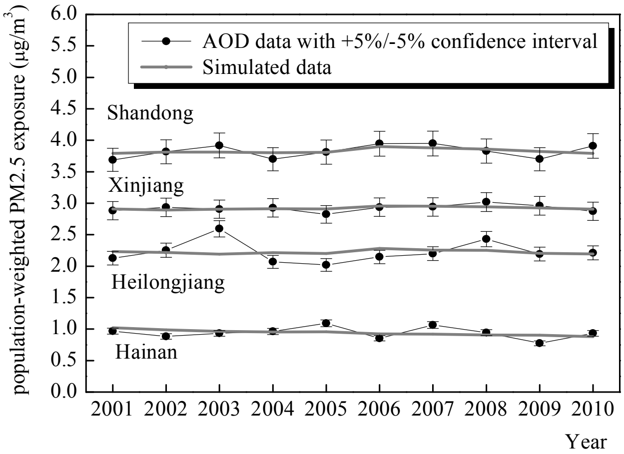

Fig. 2: Difference between AOD population-weighted PM2.5 exposure and simulated data.

LnPM contributions from LnEN, LnHI, LnCO, and LnVE.

Validate the regression model: Using the values from Tables 7 and 8, we can simulate the population-weighted PM2.5 exposure data based on the regression model in Eq.1. Shandong, Xinjiang, Heilongjiang, and Hainan were selected as examples for identifying differences between AOD PM2.5 exposure data and simulated data. Fig. 2 shows out population-weighted PM2.5 exposure data with a ±5% confidence interval and a simulated line. It shows that most of the simulated data were in the range of a ±5% confidence interval of AOD data, except for Heilongjiang and Hainan data. This explains that the regression model in our study may accurately simulate data for provinces with high AOD PM2.5 exposure.

CONCLUSIONS

PM2.5 has been an important pollution emissions index in China in recent years. As it is difficult to collect annual average PM2.5 concentrations over the past decades, we utilized satellite remote sensing data of atmospheric aerosols to determine provincial population-weighted PM2.5 exposure between 2001 and 2010 in China. Then, we tested four impact factors in China to determine regional PM2.5 exposure index via a panel data model. We arrived at the following conclusions:

1. China's 29 provinces' population-weighted PM2.5 exposure from 2001 to 2010 shows that PM2.5 levels in China were well above WHO guidelines for annual average PM2.5 exposure of 10 micro-grams per cubic meter (μg/m^3) (WHO 2006).

2. Nationally, energy consumption, highway length, and construction positively affected population-weighted PM2.5 exposure. However, the impact of each variable varied depending on the province. Vehicle possession negatively affected population-weighted PM2.5 exposure in China. This study shows that highway length may be a more important factor than vehicle possession in determining PM2.5 concentrations in China.

3. The regression model in our study may accurately simulate data for provinces with high AOD PM2.5 concentration. However, most simulated data were in the range of a ±5% confidence interval of AOD data.

4. The above conclusions show that the 29 provinces' population-weighted PM2.5 exposure varied significantly. This has many potential implications for policies in China. First, when formulating PM2.5 emission reduction policies, governments should develop different policies for each province. Secondly, improving energy efficiency and reforming industries can reduce PM2.5 emissions. Economically, China should increase energy costs, and gradually build pricing mechanisms that can reflect resource scarcity, market supply and demand, and environmental costs. These measures can provide effective and lasting incentives to reduce PM2.5 emissions. Third, China should regulate dust producing-industries during urbanization, especially in constructing new highways and buildings.

ACKNOWLEDGEMENTS

This research has been financed by the National Natural Science Fund Projects (81450022) of China and High School Funding Scheme for Key Young Teachers of Education Department of Henan Provincial Government (2015GGJS-194). The study is also supported by the Research Funds of Key Laboratory of Heating and Air Conditioning, The Education Department of Henan Province.

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